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An Efficient Approach to Face Recognition Using a Modified Center-Symmetric Local Binary Pattern (MCS-LBP)

Anusha Alapati[1] and Dae-Seong Kang[1]

[1]*Dong-A University, Dept. of Electronics Engineering, 37 Nakdong-daero 550 beon-gil Saha-gu, Busan, Korea*
dskang@dau.ac.kr

Abstract

In this paper, we present a novel face recognition method called Multi-scale block Center-Symmetric Local Binary Pattern (MCS-LBP). The face recognition process mainly consists of three phase: face representation, feature extraction, and classification. However, the most important phase is extraction, in which unique features of the face image are extracted. The Center-Symmetric Local Binary Pattern (CS-LBP) feature can be viewed as a combination of texture-based features and gradient-based features. However, it has less dimensional area; the bit-wise comparison made between two single pixel values is significantly affected by noise and sensitive to image translation and rotation. To address this problem, we present a modified feature called MCS-LBP. Instead of individual pixels, in the modified CS-LBP, the comparison is performed based on average gray values of sub-regions. Hence, it provides more complete representation than the Local Binary Pattern (LBP) and CS-LBP operator. Experiments demonstrate the proposed method.

Keywords: *Face recognition, Center-symmetric Local Binary Pattern (CS-LBP), Feature extraction, Multi-scale block Center-Symmetric Local Binary Pattern (MCS-LBP)*

1. Introduction

Face recognition is used to identify or verify a person using biometric parameters. Face recognition is successfully applied today in law enforcement, surveillance, entertainment, banking, security system access, and personal identification, among others. The most used face recognition techniques used are Eigen faces [1-3], Fisher faces [4], Laplacian faces [5], and Neural Networks [6]. In practice, there is some difficulty in dealing with different illuminations, poses, facial expressions, ageing, and so on. For human beings face recognition is an easy task, while face recognition is quite a difficult task for a computer. A digital image is made up of a finite number of elements, each of which has a particular location and value. These elements are known as pixel and picture elements and are important in face recognition.

This face recognition process mainly consists of three phases: face representation, feature extraction, and classification. Face representation refers to modeling a face, and it determines the successive algorithms of detection and identification. The entry-level recognition determines whether the given image represents a face. In the feature extraction phase, the most useful and unique features (properties) of the face image are extracted. With these obtained features, the face image is compared with the images a database. This is done in the classification phase. The output of the classification phase is the identity of a face image from the database with the highest matching score, (i.e., with the smallest differences compared to the input face image).

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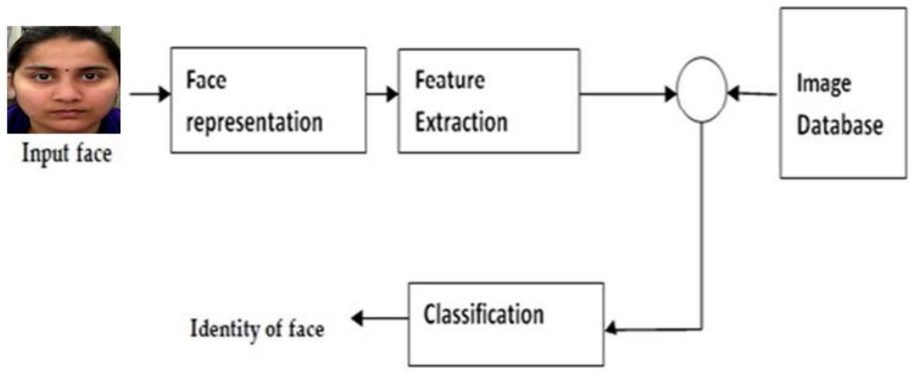


Figure 1. Identification Process with Face Recognition

The face plays a major role in our social intercourse in conveying identity and emotion. Face recognition has been a major focus of research in recent decades, because it is non-invasive in nature and it is our primary method of person identification.

Local Binary Pattern (LBP) is a popular method for image representation and classification [7]. The basic version of the LBP operator only considers the eight neighbors of a pixel, and later, this has been extended with many modified versions [8].The LBP operator, describes a long histogram; therefore, in order to use LBP as a region descriptor, Heikkilä introduced the CS-LBP operator in [9]. The proposed CS-LBP descriptor combines the good properties of SIFT and LBP, which makes it effective as a region descriptor. However, comparison based on pixel-level is greatly affected by noise and sensitive to image translation and rotation. Moreover, features calculated in the local 3x3 neighborhood cannot capture larger-scale structures (macrostructures) that may be dominant features of faces. Therefore, a novel representation, called Multi-scale Block CS-LBP (MCS-LBP), is proposed here to overcome the limitations of CS-LBP and LBP. In MCS-LBP, average gray values of sub-regions are compared instead of individual pixels.

The rest of the paper is organized as follows: In Section 2, a brief overview of the LBP and CS-LBP methods is given and MCS-LBP introduced. In Section 3, experiments and analyses are presented, and in the last section, conclusions and future research directions are presented.

2. The Proposed Method

This section presents a brief discussion of LBP, CS-LBP, and MCS-LBP.

2.1 Local Binary Patterns (LBP)

The original LBP operator was introduced by Ojala *et al*. [10, 11]. Local binary pattern LBP is a texture descriptor that codifies local primitives (*e.g.*, curved edges, spots, flat areas, *etc.*) into a feature histogram. LBP and its extensions outperform existing texture descriptors with respect to both performance and computation efficiency. In the basic version of LBP, the feature of a pixel is assigned by thresholding the 3×3-neighborhood of each pixel with the center pixel's value. This operator works with the eight neighbors of a pixel, using the value of the center pixel as a threshold. If a neighbor pixel has a higher gray value than the center pixel, then a one is assigned to that pixel; otherwise it is assigned a zero value. The LBP code for the center pixel is then produced by concatenating the eight ones or zeros to a binary code.

Let gc be the center pixel gray level and gp (i = 0, 1... 7) be the gray level of each surrounding pixel. If gp is smaller than gc, the binary result of the pixel is set to 0; otherwise, it is set to1. All the results are combined to an 8-bit binary value. The decimal value of the binary code is the LBP feature. See Figure. 2 for an illustration of computing the basic LBP feature.

$$LBP_{p,r}(x_c, y_c) = \sum_{n=0}^{7} s(g_n\text{-}g_c)2^n$$
$$s(x) = \begin{cases} 1, \ if\ x > T \\ 0, \ Otherwise \end{cases} \quad (1)$$

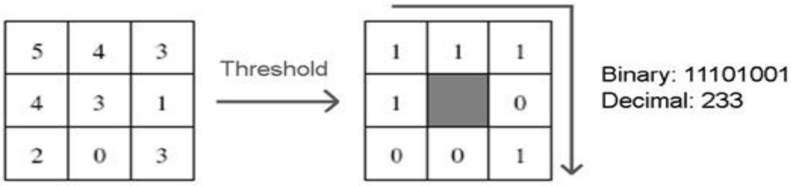


Figure 2. Basic LBP Operator

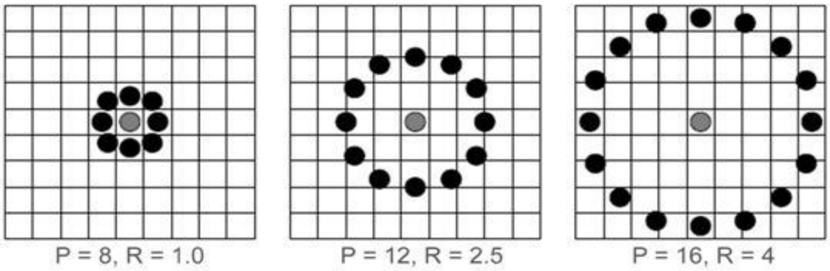


Figure 3. Circularly Symmetric Neighbor sets for Three different Values of P and R

2.2 Center-Symmetric Local Binary Patterns (CS-LBP)

CS-LBP is a modified version of LBP. In CS-LBP, instead of comparing the neighboring pixel, the center-symmetric pairs of pixels are compared, such as (g_0,g_4), (g_1,g_5), (g_2,g_6), and (g_3,g_7) in Figure 3. Robustness on flat image regions is obtained by thresholding the gray level differences with a parameter T. The CS-LBP features can be computed by Equation (2) as follows:

$$CS - LBP_{R,N,T}(x, y) = \sum_{n=0}^{3} s(g_n\text{-}g_{n+4})2^n$$
$$s(x) = \begin{cases} 1, \ if\ x \geq T \\ 0, \ Otherwise \end{cases} \quad (2)$$

Here g_n and g_{n+4} correspond to the gray level of center-symmetric pairs of pixels of a 3x3 descriptor, and "T" is a user-specified small value, that is which is used to increase the robustness of CS-LBP features on images by thresholding gray-level difference [12]. We can see that CS-LBP closely related to the gradient operator, because, like some gradient operators, it considers gray-level differences between pairs of opposite pixels in a neighborhood. Thereby, CS-LBP feature take advantage of both the properties of the LBP and the gradient-based features. The LBP and CS-LBP encoding procedures are illustrated in Figure 3.

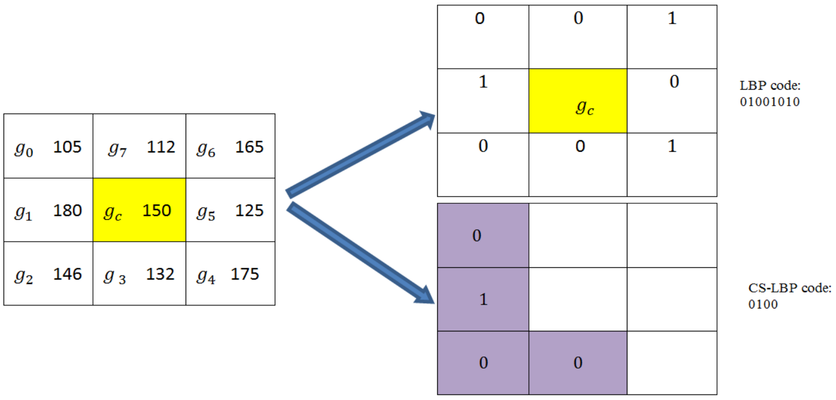


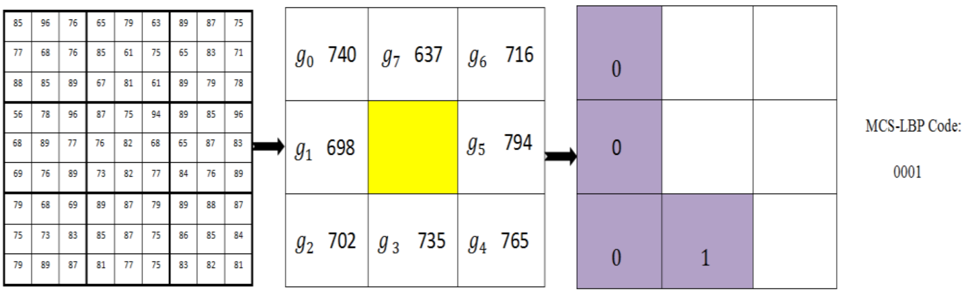
Figure 4. LBP and CS-LBP Operators

2.3 Multi-Scale Block Centre-Symmetric Local Binary Pattern (MCS-LBP)

As mentioned above, the comparison based on pixel-level is significantly affected by noise and sensitive to image translation and rotation. In MCS-LBP, the comparison between single pixels in CS-LBP is replaced with a comparison between average gray values of sub-regions. In order to simplify the computation, we use the sum instead of average gray value of each sub-region. Each sub-region is a square block containing neighboring pixels. The whole filter contains nine blocks. We take the side length, L, of the block as a parameter, with 9 L L denoting the scale of the MCS-LBP operator (particularly, 9 1 1 MCS-LBP is used in the original CS-LBP). The computational process can be expressed in Equation 3.

$$B = \sum_{k=0}^{8} g_k$$
$$MCS-LBP = \sum_{n=0}^{3} s(B_n - B_{n+4})2^n \qquad (3)$$
$$s(x) = \begin{cases} 1, x \geq T \\ 0, otherwise \end{cases}$$

where, g is the gray values of individual pixels and B is the sum of the nth value.



(a) (b (c)

Figure 5. The MCS-LBP Operator (a) The Original 3x3 Gray Values (b) Computation of the Sum of Gray Values of Each Block (c) Comparison of Center-Symmetric Pairs of Pixels and Derivation of MCS-LBP Code.

After calculating the sum of the pixels of the blocks, computed center-symmetric pairs of blocks (B) are compared, such as (B_0,B_4), (B_1,B_5), (B_2,B_6), and (B_3,B_7) In order to simplify the computation, we use the sum instead of average of gray values of each sub-region. A 3x3 MCS-LBP detailed procedure is explained in Figure 5.

2.4 Modified MCS-LBP Algorithm

Input:

1. Take input image I(x,y)
2. Initialize Temp (T) //T is thresholding to increase the robustness of CS-LBP flat images. In the present research, t=0.5//
3. Initialize (extract) reference pattern Histogram H=0
4. Divide image into number of sub- regions
5. For each sub-region B (3x3), calculate sum:

   where $B = \sum_{k=0}^{n} g_k$// g is the gray values of individual pixels and B is the sum of the nth value
6. Compare calculated Center-symmetric pairs of blocks(B) such as (B_0,B_4), (B_1,B_5), (B_2,B_6), and (B_3,B_7)

$$MCS-LBP = \sum_{n=0}^{3} S(B_n - B_{n+4})2^n$$

7. Compute $s(x) = \begin{cases} 1, x \geq T \\ 0, otherwise \end{cases}$
8. Calculate MCS-LBP histogram pattern of each image in the sequence I(x,y)
9. Find the highest MCS-LBP feature for each face image and combine into a single vector.
10. Compare with test face image.

Output: Feature extracted from face image (video) and compared with neighborhood pixel and recognition with unknown face.

2.5 Chi-Square Distance (X2)

The above MCS-LBP provides a brief overview of algorithm; further processing is needed for classification of point of view. In this paper, Chi-square Distance (X2) is delicately used. This has been successfully used for texture and face classification [13, 14], near-image identification [15], local descriptors matching [16], shape classification [17], and boundary detection [18].

In many natural histograms, the difference between large bins is less important than the difference between small bins, and it should be reduced. (X2) is a histogram distance that considers this. It is defined as follows:

$$\chi^2(x,y) = \frac{1}{2}\sum\frac{(x_i - y_i)^2}{(x_i + y_i)} \quad (4)$$

The X2 histogram distance comes from the X2 test-statistic, where it is used to test the fit between a distribution and observed frequencies. The X2 histogram distance is one of the distance measures that can be used to find dissimilarity between two histograms.

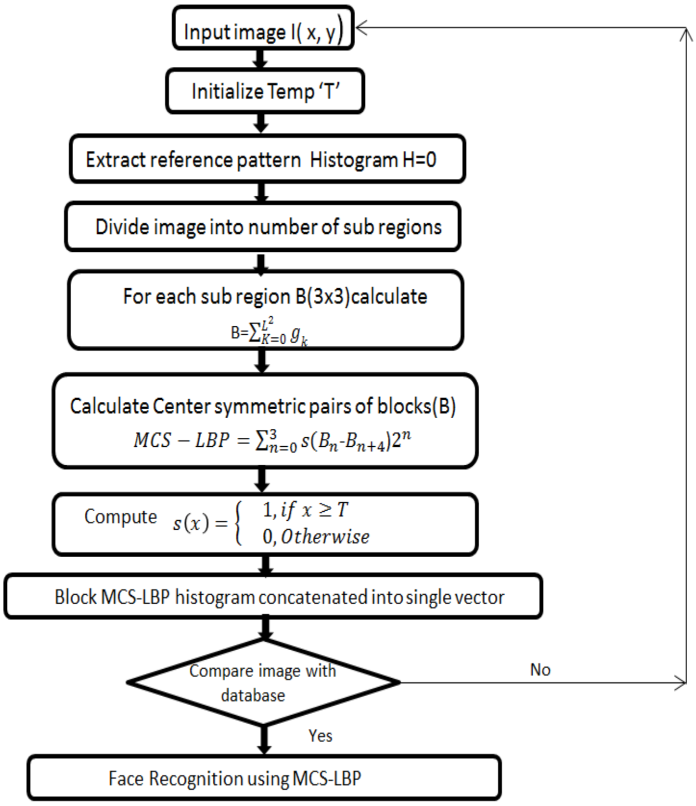
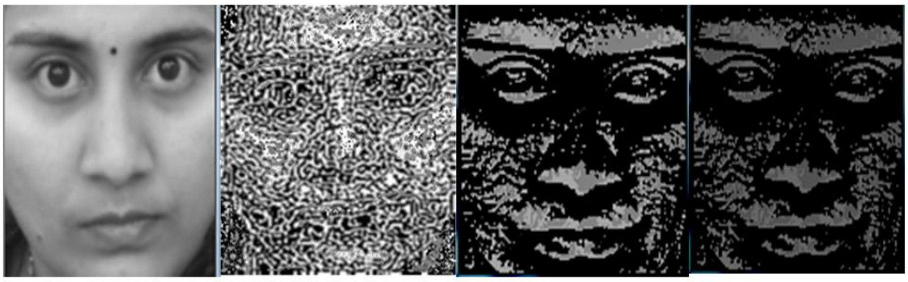


Figure 6. Flowchart of Proposed System

3. Experimental Results

3.1 Face Description with MCS-LBP

In MCS-LBP, the comparison operator between single pixels in CS-LBP is simply replaced with a comparison operator between average gray values of sub-regions (Figure 4). Each sub-region is a square block containing neighboring pixels (or just one specific pixel). The whole filter is composed of nine blocks. We take the size L of the filter as a parameter, and L×L denotes the scale of the MB-LBP operator (3×3 MCS-LBP is in fact the original CS-LBP). Note that the scalar values of averages over blocks can be computed very efficiently from the summed area or integral image [19]. For this reason, MCS-LBP feature extraction can also be very fast, and it only incurs a lightly higher cost than the original 3×3 CS-LBP operator. Figure 2 gives examples of MB-LBP filtered face images by 3×3, 9×9 and 15×15 blocks. From these examples, the influence of parameter L is determined. For a small scale, local micro patterns of a face structure are well represented, which may beneficial for discriminating local details of faces. On the other hand, using average values over the regions, the large-scale filters reduce noise and make the representation more robust; in addition large-scale information provides complementary information to small- scale details. Nevertheless, much discriminative information is also dropped. Normally, filters of various scales should be carefully selected and then fused to achieve better performance.



(a) (b) (c) (d)

Figure 7. MCS-LBP Filtered Images with different Scales: (a) Original Image, (b) Filtered Image by 3x3 MCS-LBP Operator, (c) Filtered Image by 9x9 MCS-LBP Operator, and (d) Filtered Image by 15x15x3 MCS-LBP Operator.

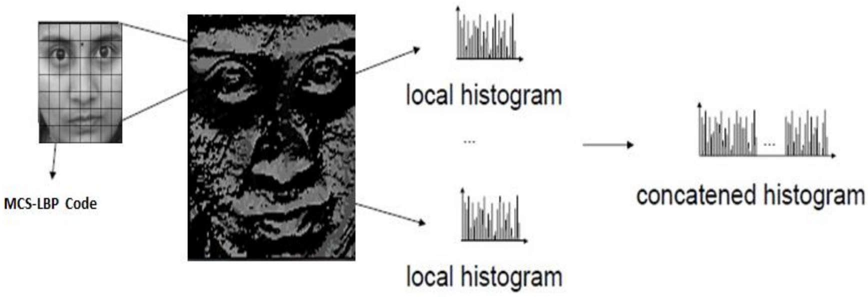


Figure 8. Histogram Extraction for 15 x 15 Regions

The MCS-LBP method presented in the previous section is used for face description. The procedure includes texture analysis, dividing a feature image into several small regions, computing the histogram of each region and concatenating the histograms of all the regions into a single feature histogram that efficiently represents the face image. Figure 8 shows the histogram extraction steps for 15 x15 regions.

3.2 Database

To build the system, we collected 600 images from nearly 30 persons a database. Some images were collected from the internet. The database included frontal and near frontal views of a person. Some face images were from one subject. Based on the algorithm, input images were compared with database face images. Below are some of the images from the database.

Figure 9. Examples of Face Images from the Face Database Considered in the Experiments

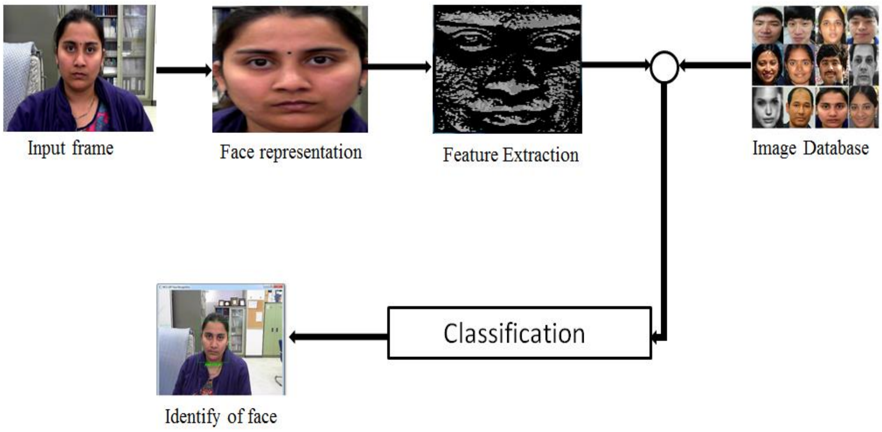


Figure 10. Step-by-Step Process of System

Table 1. Recognition Accuracy of Proposed Method Compared with Other Methods

Method	Accuracy (%)
LBP	88.7
CS-LBP	92.8
MCS-LBP	96.3

4. Conclusion

This paper presented an MCS-LBP based operator for robust image representation. a CS-LBP comparison based on pixel level is significantly affected by noise and sensitive to image translation and rotation. Therefore, in MCS-LBP, the comparison between single pixels in CS-LBP is replaced with a comparison between average gray values of sub-regions and added threshold T is added to the operator. As a result, tbe coding method changed to 3-valued .Experiments on collected images database showed that MCS-LBP significantly outperformed the LBP and CS-LBP methods.

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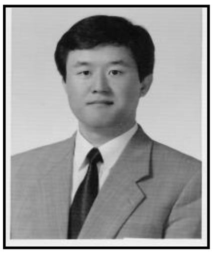
Authors

Anusha Alapati, She received her BS degree from Jawaharlal Nehru Technological University, Kakinada, India, in the year 2009. At present, she is pursuing her M.S. degree in Electronics Engineering from Dong-A University, Korea. Her research interests include image processing and object tracking.



Dae-Seong Kang, He received the BS degree from Kyungpook National University, Daegu, Korea, in 1984 and his M.S. and Ph.D. degrees in Electronics Engineering from Texas A&M University, USA, in 1991 and 1994, respectively. He has been a professor in Department of Electronics Engineering, Dong-A University. His research interests include signal and image processing, compression.

